Journal of Power Sources 236 (2013) 357–364

Contents lists available at SciVerse ScienceDirect

Journal of Power Sources

journal homepage: www.elsevier.com/locate/jpowsour

Sensitivity of plug-in hybrid electric vehicle economics to drive patterns, electric range, energy management, and charge strategies

Jeremy Neubauer*, Aaron Brooker, Eric Wood

National Renewable Energy Laboratory, Energy Storage, 1617 Cole Blvd., Golden, CO 80401, USA

HIGHLIGHTS

- ► Detailed PHEV economics modeling and comparison to the cost of conventional vehicles.
- ► Considers real-world drive patterns, battery wear, and battery replacement.
- ► Driver- or vehicle-specific usage patterns are necessary for accurate economic analyses.
- ► Battery replacements are rarely justified economically, even with very low battery prices.
- ► Limited all-electric range PHEVs consume much less gasoline than a conventional vehicle.

ARTICLE INFO

Article history:
Received 2 April 2012
Received in revised form
17 July 2012
Accepted 19 July 2012
Available online 27 July 2012

Keywords:
Battery Ownership Model
Total cost of ownership
Plug-in hybrid electric vehicles
Charge strategies
Drive pattern
Range

ABSTRACT

Plug-in hybrid electric vehicles (PHEVs) offer the potential to reduce oil imports, greenhouse gases, and fuel costs, but high upfront costs discourage many potential purchasers. Making an economic comparison with conventional alternatives is complicated in part by sensitivity to drive patterns, vehicle range, available energy management, and charge strategies that affect battery wear and gasoline consumption. Identifying justifiable battery replacement schedules adds further complexity to the issue. The National Renewable Energy Laboratory developed the Battery Ownership Model to address these and related questions. The Battery Ownership Model is applied here to examine the sensitivity of PHEV economics to drive patterns, vehicle range, available energy management, and charge strategies when a high-fidelity battery degradation model and financially justified battery replacement schedules are employed. We find that energy management methodology, all-electric range, maximum beginning-of-life state of charge, and basic charge timing generally have a small impact on the total cost of ownership of PHEVs; however, PHEV economics do prove sensitive to drive patterns and the availability of an at-work charger.

1. Introduction

Although there are many reasons why an individual car buyer chooses one vehicle over another, economics is an important factor for many consumers. For some end-users, such as fleet managers, total lifetime economics is one of the top factors affecting purchase decisions. In addition, understanding the economics of technologies that can support meeting broad societal objectives, such as the reduction of oil imports and greenhouse gases, can aid policymakers in decision-making. Thus, there is a strong motivation to examine and compare the economics of today's and tomorrow's vehicle technologies.

Plug-in electric vehicles, which include both plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs), offer the potential to reduce both oil imports and greenhouse gases, but assessing their economics is complicated by several factors. For one, plug-in electric vehicle batteries – typically a major component of total vehicle ownership costs – are subject to complex operational duty cycles specific to vehicle platform and driving habits, making battery life difficult to forecast. Further complicating battery life calculations are a battery's sensitivity to local climate and charge strategy, the proposals of some to reap revenue from vehicle-to-grid and vehicle-to-building services, and the potential for second use revenue generation following the end of its automotive service life.

For PHEVs with a limited all-electric operational mode, electricity and gasoline costs become highly sensitive to the distribution of daily vehicle miles traveled (DVMT) experienced over the life of the vehicle, herein referred to as a drive pattern. For example, some drivers may be able to complete the majority of their driving needs with a modest all-electric range (AER), thus using very little gasoline, while other drivers may do just the opposite. A BEV on the other hand, may require a driver to adapt his or her drive patterns

* Corresponding author. Tel.: +1 720 989 1919.
E-mail addresses: Jeremy.neubauer@nrel.gov, jeremy.s.neubauer@gmail.com (J. Neubauer).

0378-7753/$ – see front matter
http://dx.doi.org/10.1016/j.jpowsour.2012.07.055

to the limited total range of the vehicle, or alternatively turn to fast charge or battery swapping options to complete long trips. Such techniques drastically complicate economic computations by introducing significant infrastructure requirements and inserting additional parties into the equation.

With support from the Vehicle Technologies Program in the U.S. Department of Energy, the National Renewable Energy Laboratory has developed a vehicle total cost of ownership (TCO) calculator known as the Battery Ownership Model (BOM) to address these and other challenges associated with the lifecycle economics of electric vehicles. In this paper, we apply the BOM to examine the sensitivity of PHEV economics to drive patterns, range, available energy management, and charge strategies when a high-fidelity battery degradation model and financially justified battery replacement schedules are employed.

2. Approach

The BOM is an advanced TCO calculator that takes into account various scenarios of vehicle and component costs, battery and fuel price forecasts, drive patterns, battery wear, charging infrastructure costs, purchase incentives, financing, ownership, and other criteria. The vehicle economics considered include vehicle and related infrastructure purchases, financing, fuel (gasoline and electricity) costs, non-fuel operating and maintenance costs, battery replacement, salvage value, and any costs passed on by a third party such as a service provider to account for the installation, use, and availability of infrastructure. Battery degradation, charging strategies, and drive patterns play an important role in each of these elements and are addressed as described below. An approximate graphical representation of the key elements and flow of data within the BOM is illustrated in Fig. 1.

A more detailed description of these elements can be found in O'Keefe et al. [1]. The vehicle performance and sizing model included is the National Renewable Energy Laboratory's Future Automotive Systems Technology Simulator (FASTSim) developed under funding provided by the Vehicle Technologies Program in the U.S. Department of Energy. Note that the battery second use and vehicle-to-grid elements are recent additions not described therein; discussion and use of these modules will be presented in future papers. In addition, the battery use and wear element has recently received considerable updates, as discussed below.

2.1. Cost metrics

The primary output of the BOM is the ratio of the total discounted costs of an advanced vehicle – in this discussion a PHEV – to that of a conventional vehicle (CV), as defined in Equation (1). The variable c_i is the cost to the vehicle owner/operator during the given period, i. The discount factor for the given period is d_i, and the total number of periods is N.

$$\text{PHEV} - \text{to} - \text{CV Cost ratio} = \frac{\left(\sum_{i=1}^{N} c_i \cdot d_i\right)_{\text{PHEV}}}{\left(\sum_{i=1}^{N} c_i \cdot d_i\right)_{\text{CV}}} \quad (1)$$

When using this approach, it is important that the inputs and assumptions applied to the calculation of the PHEV and CV costs are identical, such that the calculated cost ratio is indicative of the relative cost of replacing a specific individual CV subject to a particular drive pattern with a PHEV operated under identical conditions and requirements.

When the period of analysis covers the entire lifetime of a vehicle as is done herein, this use of TCO is advantageous for assessing the total merit of PEV technologies over their entire lifetime and evaluating economic trends resultant from varied technical configurations and use strategies, as is the intent of this study. However, it is worthwhile to note that consumer purchase decisions may be more influenced by the evaluation of payback periods over shorter ownership durations. As such an approach introduces additional variables and can distort relationships in a manner detrimental to our prime intent, we exclude the payback period approach from this investigation.

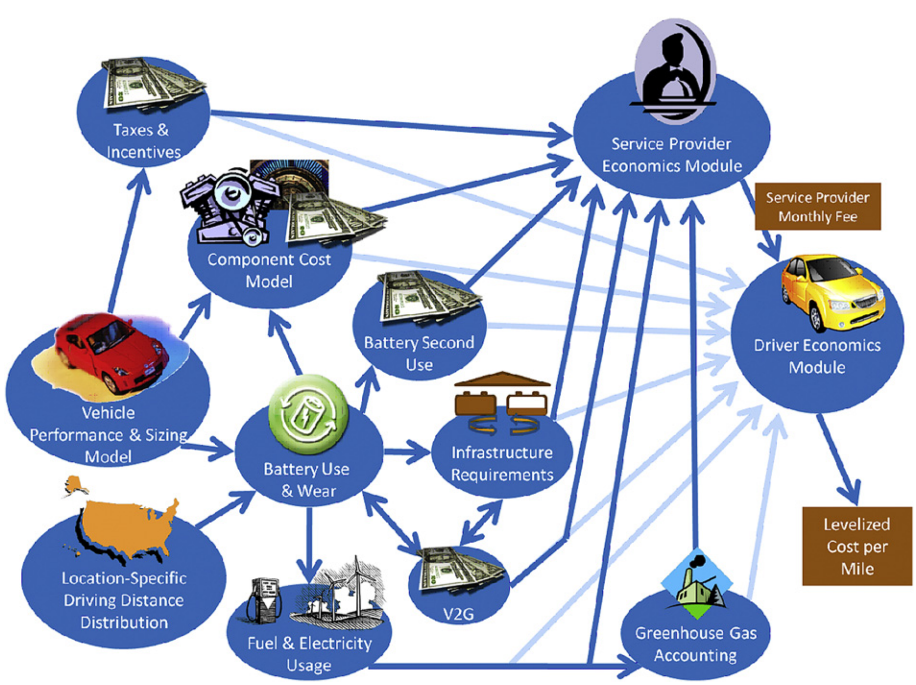

Fig. 1. Key elements and data flow within the Battery Ownership Model.

2.2. General variables

In all economic analyses we examine a 15-year period of ownership covering the entire assumed life of the vehicle. A driver discount rate of 8% is assumed, as are national average temperatures and tax rates for battery purchases, vehicle purchases, and vehicle registration. Where a 2012 start year is assumed, a federal tax credit range from $2500 to $7500 as a function of battery energy per [2] is applied. When a 2015 start year is assumed, no federal tax credit or other purchase incentives are considered.

2.3. Battery degradation and replacement

A high-fidelity degradation model [3] for nickel–cobalt–aluminum cathode/graphite anode lithium ion batteries capable of considering complex duty cycles and accurately capturing the impact of depth of discharge (DOD), temperature, and state of charge (SOC) has been incorporated into the BOM. Note that the effects of voltage are captured by accounting for the SOC history of the battery. Each of these factors has been shown to strongly affect battery performance over time, often in a nonlinear fashion, yet are commonly ignored or coarsely estimated in previous TCO studies. The effect of charge and discharge rate, which has not been directly incorporated into our employed degradation model, is assumed to have a minimal affect over the range of operational conditions explored herein.

In the BOM, our degradation model calculates capacity loss and resistance growth at the end of each service year based on the selected drive pattern, charge strategy, and environmental conditions, which are used in turn to compute the annual all-electric vehicle miles traveled (VMT) achievable by the PHEV each year. The maximum charge SOC and timing of charge operations are selectively set as discussed later. Minimum SOC is adjusted each year such that no less than 80% of BOL power can be delivered at the end of charge depleting operation. Thus, minimum SOC generally increases over time as resistance grows. In this manner, we translate the effect of power fade to a reduction in available energy, and thereby vehicle range.

We leverage this capability to employ bounded, cost-optimal battery replacement schedules. The BOM first calculates the degradation and resultant available energy of the battery for each year up to a prescribed technical limit. In this study, that limit is defined by reaching a 15-year calendar limit or the loss of 50% of initial battery capacity. The 15-year calendar limit is selected to be coincident with the life of the vehicle, while the 50% of initial battery capacity limit is intended to represent the point at which the battery begins to degrade at a vastly accelerated rate and may no longer be safe for automotive use. Alternative values could be employed, preferably justified by life test data; however, such data are not available at present. The TCO is then computed for each possible automotive service tenure up to this limit, and the point at which TCO is minimized is employed for determining battery replacements. Note that a labor cost of $500 is included for each battery replacement in the TCO calculations, representative of a single technician working approximately 5 h at a loaded rate of $100 hr^{-1} [4]. This framework therefore represents a cost-justified approach to determining battery life, rather than the arbitrary election of time, mileage, or capacity limits that may be inappropriate for accurate economic analyses.

2.4. Gasoline and electricity prices

National average gasoline price forecasts, as reported in the Energy Information Administration's (EIA's) 2011 high oil price scenario [5], are employed to calculate recurring energy costs. This scenario is selected as it best agrees with the EIA's reported actual 2011 gasoline costs [6]. Electricity price projections from the EIA's 2011 baseline scenario are used to calculate energy costs, as its 2011 values agreed well with actual prices [6]. Both the gasoline and electricity prices employed in this study are shown in Fig. 2.

2.5. Electric range

The economics of PHEVs and CVs are innately different – PHEVs generally exhibit a high upfront cost but low operating costs, and CVs vice versa. Thus, increasing the total all-electric VMT achieved with a PHEV is a path toward improving the PHEV-to-CV cost ratio. We expect that the AER of the PHEV will impact this cost ratio on the basis that a larger range will enable more all-electric VMT, but incur higher upfront costs while also impacting battery life. To assess this dependency, we simulate four PHEVs with AERs of 15, 25, 35, and 45 miles.

Although the selection of this set of AERs was guided by both the United States Advanced Battery Consortium's PHEV AER targets [21], as well as current and upcoming commercial PHEV offerings, we stress that this study is not a target evaluation, nor a comparison of any specific manufacturer's vehicle models. Differences in vehicle platforms, control strategies, and other factors between our assumptions, the assumptions behind the United States Advanced Battery Consortium target analysis [22], and actual available vehicle values can strongly affect the results we present herein.

2.6. Charge strategy

Charge strategies can also affect economics via recurring costs, upfront costs, and achieved mileage. Adjusting the timing of charge events can extend battery life and reduce battery replacement costs. For a prescribed range, raising the maximum allowed beginning-of-life (BOL) SOC of the battery will decrease battery size and thereby initial cost, but will shorten battery life by increasing both exposure to higher voltages and the DOD of each cycle. Increasing the frequency of charging (e.g., charging both at home and at work) can effectively increase the all-electric VMT of a PHEV, but will affect battery life by increasing the number of cycles and generally reducing the DOD.

While minimum BOL SOC is set to 20% for all cases, we vary the maximum BOL SOC limit of the battery from 85% to 100% in 5% increments. Note that battery size is increased as maximum BOL SOC is decreased to maintain the prescribed range of 15, 25, 35, or 45 miles. This effectively assumes, that the vehicle manufacturer is planning for and controlling maximum BOL SOC rather than the end user controlling it and will pit extensions of battery longevity against the increased upfront cost of a larger battery.

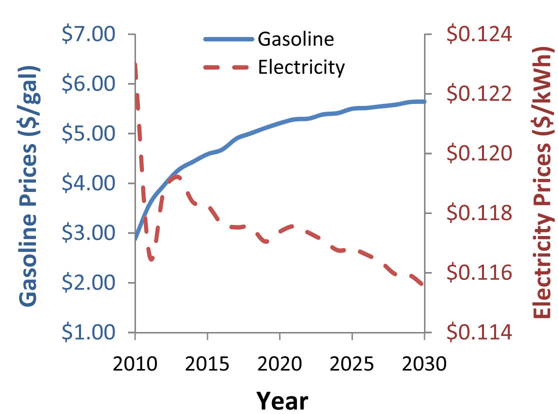

Fig. 2. Employed retail gasoline and electricity prices (2012 dollars).

Three different charge timings are employed as well, as summarized in Table 1. The first charge strategy (CS1) is right-away charge at home, where charging is initiated immediately when a vehicle returns home. Second (CS2) is just-in-time charge at home, where charge is initiated such that the battery reaches its maximum SOC concurrently with the time of departure. To make these bounding cases for right-away and just-in-time charge methodologies, we assume that no time is spent at a destination; thus, the rest time at either the maximum SOC (right-away) or the day's minimum SOC (just-in-time) is calculated by subtracting the required drive and charge time from a 24-hour period.

Third (CS3) is the combination of just-in-time charge at home and right-away charge at work. In this final scenario we identify work days as those where the DVMT is between one and two times the mode distance of the drive pattern. On these days we assume that half of the mode distance is traveled in the morning, followed by an 8-hour stay at work, then the remainder of the DVMT is completed prior to returning home. Charging is initiated immediately upon arriving at work, whereas at-home charging is delayed to achieve the maximum SOC concurrently with leaving for the first trip on the subsequent day.

When this third charge strategy is implemented, the cost of the at-work charger and electricity for the at-work charging is not accounted for. This is done to provide a best-case scenario on the assumption that the infrastructure and electricity are provided by the government or employer as a benefit for driving a plug-in electric vehicle. We acknowledge that this may only be applicable to select early adopters and may not apply in the long term on a larger scale. Accurately accounting for these costs requires consideration of a third party responsible for the necessary infrastructure and electricity of the at-work charge point, its commercial electricity prices, hardware costs, approach to financing, return on equity, etc., which will be addressed in a future publication. It is not expected that including these costs will substantially affect our results, however, particularly given that we assume the vehicles are charged from a simple 110 V/15 A outlet that requires no specialized charging hardware, and thus no associated charger costs.

An assumed maximum charge power of 1.4 kW (at the battery) determines the required charge time. This approximates an 85% efficient charger attached to a 15 amp, 120 V connection when an allowance for a reduced power taper charge is considered near the end of charge. Note that the charger efficiency is accounted for when computing the amount of electricity consumed from the grid. Under these assumptions, the required charge time is approximately 10.3 h or less for all vehicles in this study, which allows a complete recharge of the battery based on the average home related dwell time reported in [7]. Drive time is computed by dividing the DVMT by an assumed average speed of 42 miles per hour. This speed is chosen to be representative of 55% city and 45% highway driving per [8], which aligns with our calculation of vehicle efficiency.

2.7. Available energy management

In addition to range, maximum BOL SOC, and charge timing, we also explore the effect of two different available energy management strategies. The first strategy holds the maximum BOL SOC constant over the entire life of the vehicle. The minimum SOC is not allowed to fall below its BOL setting of 20%. Instead, it increases over time as resistance grows to ensure that 80% of BOL power can be delivered at the end of charge depleting mode operation. The second strategy, however, actively adjusts these limits in an attempt to minimize the year-to-year variance in AER. As the battery loses available capacity, the minimum SOC is first lowered while not conflicting with the requirement to provide 80% of BOL power. Once the power requirement begins setting the minimum SOC, the maximum SOC is raised (to $\leq$100%). All adjustments are made once per year in increments necessary to maintain the BOL all-electric range.

Table 1
Employed charge strategies.

Abbreviation	Description
CS1	Right-away charge at home
CS2	Just-in-time charge at home
CS3[a]	Just-in-time charge at home, right-away charge at work

[a] Note that the cost of the charger and electricity at work are not accounted for in economic computations.

2.8. Vehicle performance and cost

We assume a vehicle platform sized similarly to that of a Chevrolet Cruze. A glider mass of 1139 kg, coefficient of drag of 0.29, and total frontal area of 2.27 m^2 are employed in the simulation. Battery, motor, power electronics, and internal combustion engine specifications are calculated to achieve a 0–60 mph acceleration time of 9 s and an AER specific to the case at hand. Vehicle electricity and fuel consumption are calculated via simulation of both the highway and urban driving dynamometer schedule weighted and combined to effectively recreate the U.S. Environmental Protection Agency window sticker rating [9] under both charge depleting and charge-sustaining operational modes. A constant auxiliary load of 300 W is included during drive cycle simulation, representative of only minimal system loads exclusive of cabin heating or air conditioning [10]. Tire and maintenance costs are set at $0.0533 per mile for both CVs and PHEVs, per the AAA's 2010 estimate of typical mid-size car costs [11].

All PHEVs in this study are parallel hybrids, where an Atkinson cycle combustion engine and a single electric motor–generator are each mechanically coupled to drive the wheels. We specify a degree of hybridization of 50%, such that the combustion engine and electric motor are sized equivalently with respect to peak power. The drivetrain is capable of regenerative braking.

Battery and electric drivetrain manufacturing costs are computed based upon these results, the selected start year, and the cost schedule shown in Fig. 3, the latter adapted from the U.S. Department of Energy's future component cost targets [12,13]. This yields a cost of \$500 kWh^{-1} for batteries and \$16.2 kW^{-1} for power electronics at the initial point of purchase under the 2012 start year assumption, or \$270 kWh^{-1} for batteries and \$12 kW^{-1} for power electronics under the 2015 start year assumption. The cost of the conventional drivetrain is calculated based upon a study of currently and recently available CVs, hybrid electric vehicles, and PHEVs [20] which suggests that the cost of conventional drivetrains are reasonably well estimated by combining a flat fee of $531 with a fee that scales with engine power at the rate of \$14.5 kW^{-1} when a manufacturing-to-retail markup factor of 1.5 is applied [14–16] as we include here. This same data can be used to calculate a glider price of $14,715.50 (not subject to the 1.5 manufacturing-to-retail markup factor) for the midsize vehicle class we consider.

Note that the future battery costs are important for computing the cost of battery replacements and battery salvage value when applicable. In this study, when a battery's end of life does not coincide with the end of our 15-year analysis period, we calculate the remaining automotive value of a battery by prorating its remaining life against the cost of new batteries at the 15-year driver time horizon, then discount that value by 25%. This accounts for the fact that the battery can be removed from the chassis at the end of the chassis' usable lifetime and sold for use in a different automobile. However, we ignore the cost or value of battery recycling

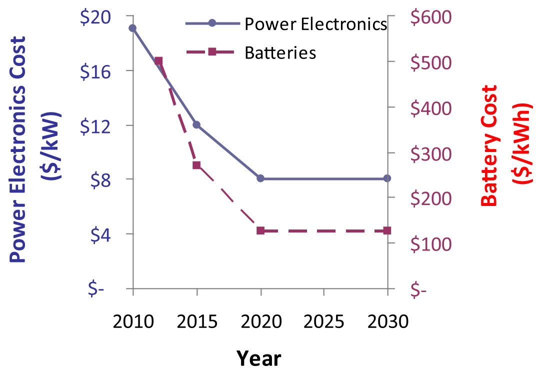

Fig. 3. Battery pack and power electronics manufactured cost schedule.

and second use subsequent to the battery's end of life due to the high level of uncertainty involved. The errors associated with this assumption are expected to be small due to the low relative cost of recycling and the impact of the time value of money.

For calculation of the PHEV-to-CV cost ratio, we also simulate a CV under identical technical and economic assumptions, sized using the same glider assumptions and 9 s 0–60 mph target but powered solely by an internal combustion powered drivetrain. The resultant CV demonstrates 32 miles per gallon with a calculated retail price of $17,687, similar to that of a Chevrolet Cruze. The CV and PHEV vehicle specifications are summarized in Table 2.

2.9. Employed driving data

The BOM requires that a drive pattern in the form of a DVMT probability distribution function (PDF) be input for calculating total miles traveled, total all-electric miles traveled, battery wear, etc. As we showed in [17], variation among different DVMT PDFs has a significant impact on the economics of BEVs. Accordingly, in this study we employ real world driving data collected from the Puget Sound Regional Council's 2007 Traffic Choices Study (TCS) to generate the necessary DVMT PDFs [18].

The TCS was an investigation of the response of travel behavior to variable toll charges in the Seattle metropolitan area. The study placed global positioning systems in 445 vehicles from 275 volunteer households that recorded driving data over an 18-month average per household period. The experiment started with a baseline period in which no artificial tolls were applied to affect behavior. We process the data for use in this study by (1) only considering data collected during the approximately 3-month baseline period, (2) eliminating vehicles for which no driving took place during the baseline period, (3) eliminating vehicles for which significant errors in data recording were identified, and (4) reducing detailed trip data to DVMT based upon the length of each trip and the date on which it was started. The resultant data are then converted into 398 longitudinal (one vehicle, multiple days) discrete DVMT PDFs for use by the BOM. For comparison purposes, the DVMT of each of the 398 vehicles are combined to create a cross-sectional DVMT PDF representative of the fleet of TCS vehicles. A cross-sectional DVMT PDF is created from the 2001 National Highway Travel Survey data as well [19]. Additional information on the characteristics of this dataset can be found in [17].

The primary shortcomings of the TCS data as we use it are that (1) each drive pattern does not fully capture seasonal variations, (2) it does not account for changes in driving behavior as the vehicle ages, and (3) sampling biases imply the data may not fairly represent the distribution of income levels, household size, proximity to public transit, etc., beyond or even within the Seattle area. These factors prevent our analysis from making blanket statements regarding the overall cost-effectiveness of PHEVs at the national level; however, they do not prevent a valuable demonstration and exploration of the sensitivity of PHEV economics to drive patterns, vehicle range, charge strategies and other factors as is done herein.

Table 2
Vehicle specifications.

Vehicle	Electric range (mi)	Maximum SOC	Engine power (kW)	Motor power (kW)	Battery energy (kWh)	2012 Vehicle retail price	2015 Vehicle retail price
CV	0	n/a	100	0	0	$17,687	$17,687
PHEV15	15	100%	43.4	43.4	5.6	$21,682	$19,490
		95%	43.4	43.4	6.0	$21,965	$19,643
		90%	43.3	43.3	6.4	$22,283	$19,812
		85%	43.7	43.7	6.9	$22,679	$20,033
PHEV25	25	100%	44.6	44.6	9.5	$24,707	$21,142
		95%	45.1	45.1	10.2	$25,217	$21,424
		90%	45.5	45.5	11.0	$25,797	$21,744
		85%	45.5	45.5	11.8	$26,446	$22,094
PHEV35	35	100%	46.0	46.0	13.5	$27,766	$22,814
		95%	46.4	46.4	14.5	$28,487	$23,210
		90%	46.9	46.9	15.5	$29,312	$23,662
		85%	47.3	47.3	16.8	$30,266	$24,184
PHEV45	45	100%	47.8	47.8	17.6	$30,900	$24,533
		95%	48.0	48.0	18.8	$31,829	$25,038
		90%	48.4	48.4	20.2	$32,903	$25,624
		85%	49.4	49.4	22.1	$34,386	$26,438

3. Results and discussion

To study the interplay of four vehicle ranges, four maximum SOCs, three charge timing schedules, and two available energy management strategies with 398 driving patterns over two different start year scenarios, we simulate 76,416 unique cases. Presentation and interpretation of this many data points can be challenging. For a specific set of assumptions, it is useful to inspect a single cumulative distribution function of all 398 drive patterns. However, discussion of 192 cumulative distribution functions covering all combinations of range, charge strategies, available energy management strategies, and start years is not straightforward either. We therefore employ a 75th percentile PHEV-to-CV cost ratio metric, for which 25% of all vehicle drive patterns exhibit a lower PHEV-to-CV cost ratio.

3.1. Battery lifetime

In nearly all of the 76,416 cases simulated, the cost-optimal battery replacement algorithm resulted in a battery automotive service life equal to that of the vehicle itself; i.e. it is neither cost effective to replace the battery within the lifetime of the vehicle, nor does the battery capacity fall below our imposed 50% minimum capacity limit.

The sole exception is the PHEV15 when operated under the CS3 charge strategy, where the short AER and the ability to charge both at work and at home conspire to subject the battery to two large DOD discharges on most days. Here, battery replacement is found to be most frequent when operated to higher maximum BOL SOCs (that accelerate battery wear) and when the 2015 start year is applied (lower cost of replacement batteries). Even under the worst case scenario, though, battery replacement only occurs for 25% of simulated drive patterns. Within this subset, not a single case produced degradation rates high enough to reach our imposed 50% minimum capacity limit over the 15-year analysis period. Rather, every PHEV15 battery replacement was economically incentivized—the economic benefit of completing more miles on

electricity that comes from replacing a degraded battery outweighed the cost of a new battery.

We do note, however, that the life test data upon which our battery degradation model is built extends at a maximum to a 9 year testing duration and records a minimum remaining capacity of 75%. Thus, our methods rely in part on extrapolation of observed trends and the continuation of inferred battery degradation mechanisms. It is possible that additional degradation mechanisms not yet observed in the underlying data could arise in the later years of vehicle ownership, causing accelerated battery wear. This, in turn, could incite a higher frequency of battery replacements than reported here.

3.2. Available energy management strategy

Switching from a static to a variable SOC limit strategy creates a complex interplay among several factors that can affect TCO, including increased DOD, decreased average SOC, and the value of electric miles over time. Our simulations show that the variable SOC limit strategy improves economics under nearly all scenarios, but the effect is generally small (<1%) as shown in Fig. 4. Based on this, and the fact that the unquantified customer satisfaction benefit of a more consistent AER early in life will likely add to the positive benefits of the variable SOC limit strategy, we restrict further investigation to this scenario from here on.

3.3. Effect of drive pattern

To assess the effect of drive pattern, we employ a drive pattern impact metric defined as the ratio between the least and most cost effective drive patterns for a given vehicle range and charge strategy. This can be thought of as a comparison of the cost effectiveness of a given PHEV scenario between the particular drivers most and least suited to that scenario. The minimum value this metric can have—one—represents complete insensitivity to drive pattern, while higher numbers indicate increased sensitivity to driver behavior. For example, a drive pattern impact factor of two reveals that the worst (highest) calculated PHEV-to-CV cost ratio is twice that of the best (lowest) calculated PHEV-to-CV cost ratio when only the drive pattern is varied, implying that a potential PHEV consumer concerned about the economics of their pending purchase decision would be well advised to consider their driving patterns in some detail.

For the scenarios investigated in this study we find that the drive pattern impact factor varies from 1.27 to 1.64, as shown in Fig. 5. These values are comparable to the drive pattern sensitivity observed for BEVs operated under the low cost of unachievable VMT as reported in [17]. Note that we only show data for the 2012 start year as the drive pattern impact factor is essentially unaffected by a switch to the 2015 start year. However, some sensitivity to vehicle range and charge strategy is noticeable—drive pattern sensitivity increases with increased range and with the addition of at-work charging. This is to be expected. As AER is increased, some drive patterns (with a high frequency of DVMT near the longer AER) increase their achieved all-electric VMT dramatically and thereby benefit economically, while others (with a high frequency of DVMT either less than the shorter AER or much greater than the longer AER) see a smaller relative effect on all-electric VMT and thus may even degrade their economics due to the higher upfront battery cost. As at-work charging is added, drive patterns consisting predominantly of work commuting will increase their achieved all-electric VMT, while those with minimal or no work commuting will not. Both of these factors work to increase the spread of PHEV-to-CV cost ratios among the 398 simulated drive patterns.

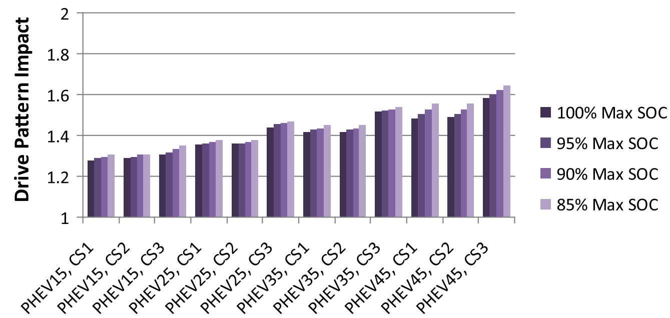

Fig. 5. Ratio of highest to lowest BEV-to-CV cost ratio for 2012 start year.

Calculation of the PHEV-to-CV cost ratio using cross-sectional TCS and National Highway Travel Survey drive patterns overestimates the PHEV-to-CV cost ratio for 39%–48% and 45%–52% of the results produced using vehicle specific longitudinal TCS drive patterns, respectively, for the 2012 start year. Again, the results for the 2015 start year are similar.

3.4. Effect of AER, charge timing, and maximum BOL SOC

The PHEV-to-CV cost ratios as a function of AER, charge timing, and maximum BOL SOC are presented in Figs. 6 and 7 for the 2012 and 2015 start years, respectively. Notice that there is not a significant difference in trends or absolute values as the start year changes, implying that the effect of the federal tax credit we assume available in 2012 is approximately equivalent to the reduction in battery and power electronics costs examined between 2012 and 2015.

When looking only at the cost-optimal maximum SOC within each combination of AER and the once-a-day charge timings (CS1 and CS2), the effect of AER is nearly negligible. Although there is

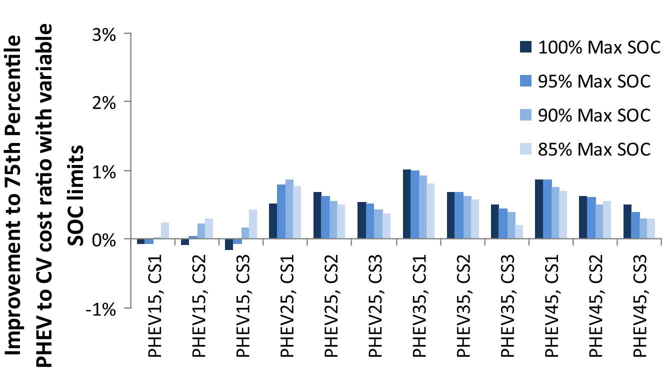

Fig. 4. Benefit to employing a variable SOC limit strategy for 2012 start year cases.

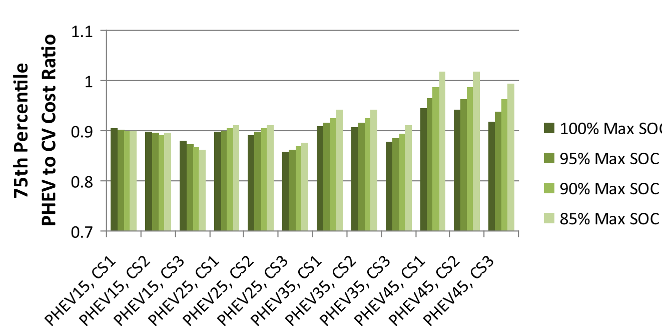

Fig. 6. PHEV-to-CV cost ratio as a function of AER, charge timing, and maximum BOL SOC for 2012 start year.

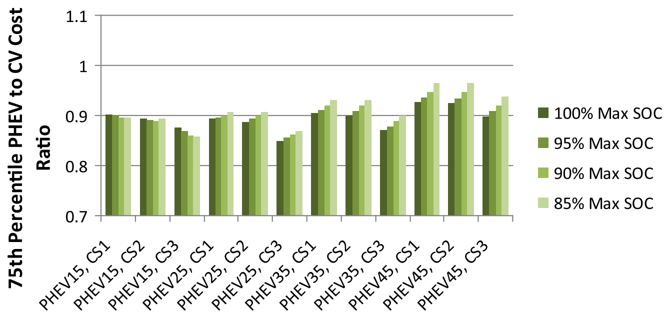

Fig. 7. PHEV-to-CV cost ratio as a function of AER, charge timing, and maximum BOL SOC for 2015 start year.

a slight economic preference toward shorter AERs, the difference in quantified value is likely to be outweighed by driver preference to complete more miles electrically, vehicle configuration, or other factors at the time of purchase. When charging at work is an option under CS3, there appears to be a slight preference for an AER near 25 miles.

The sensitivity to maximum BOL SOC is similar. As the AER is increased to 25 miles or greater, employing a maximum BOL SOC less than 100% becomes more costly. For an AER of 15 miles, however, employing a reduced maximum BOL SOC is economically advantageous. This is due to two factors. First, the benefit of reducing the maximum SOC in a PHEV15 is larger, as it experiences a higher frequency of large DOD cycles, the wear of which is strongly coupled to the maximum SOC. Thus, reducing the maximum SOC has a disproportionately larger impact on battery life for the PHEV15 duty cycle than it does for the longer range PHEVs, which experience large DODs less frequently. Second, the cost of decreasing the maximum SOC in the longer range vehicles is higher because the installed battery size is larger. However, in many cases these effects are generally small and thus may be outweighed by other factors, such as vehicle packaging requirements.

These results show that under our selected assumptions and design space, there is no single method that presents a significant opportunity to improving the economics of a PHEV. Across the spectrum of AERs, maximum SOCs, and charge strategies we study, we see only at most a 16% difference in the 75th percentile PHEV-to-CV cost ratio. This reduction from the worst to best case scenario is achieved by avoiding oversizing the battery—specifically, the combination of offering too large of an AER along with excessively restricting the maximum SOC—and enabling at-work charge opportunities. This puts the best 75th percentile PHEV-to-CV cost ratios near 0.86, making savings of 14% or more possible for 25% of the drive patterns simulated when selecting a PHEV over a CV.

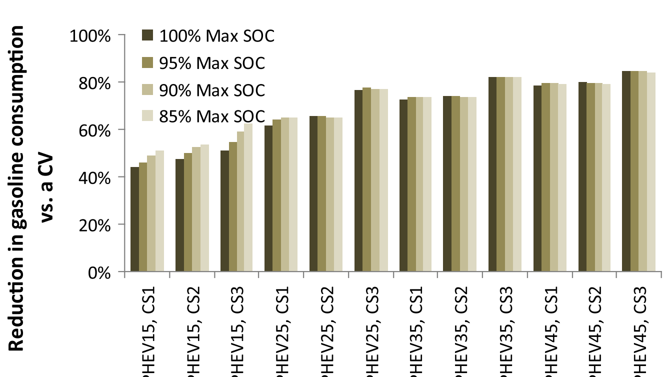

Fig. 8. Average reduction in gasoline consumption compared to a CV for the top quartile of most cost effective drive patterns.

3.5. Gasoline savings

By subtracting the fuel used by the PHEV from that used by the CV for each individual drive pattern, we can compute the percent of gasoline saved by purchasing and operating the PHEV. We perform this calculation for the top quartile of most cost-effective drive patterns under the 2012 start year, average those values, and present them below in Fig. 8. This shows a steady increase in fuel savings as AER is increased, going from an approximate 48% reduction in gasoline consumption for an AER of 15 miles operated under CS1 to an approximate 84% reduction in gasoline consumption for an AER of 45 miles operated under CS3. This corresponds to an average savings of 3371–6194 gallons per vehicle over the 15-year vehicle lifetime.

4. Conclusions

In this study we apply the National Renewable Energy Laboratory's BOM to the investigation of the sensitivity of PHEV economics to charging strategies, available energy management, vehicle range, and driving pattern. Charging strategies consider the maximum SOC, frequency of charging events, and timing of charging events as variables, while vehicle AER sweeps from 15 to 45 miles. We explore two available energy management strategies as well, one where SOC limits are static and another where they adjust annually to maintain the BOL AER. For drive patterns we employ three months of recorded data from each of 398 vehicles in the Puget Sound Regional Council's TCS. The use of this data, combined with the BOM's incorporation of a high-fidelity battery degradation model and cost-optimal battery replacement scheduling, enables this study to quantify the effects of charging strategy, vehicle range, and driving pattern not previously disclosed in the literature.

As the authors have found with BEVs in a related study [17], the TCO of PHEVs has also proven to be sensitive to drive patterns. Within the TCS dataset employed herein, we have observed that changing the drive pattern can increase the PHEV-to-CV cost ratio by up to a factor of 1.64 – a much larger impact than the variation of technical design parameters as discussed previously. We find that this sensitivity increases as the potential to complete more miles electrically grows (e.g. where AER is largest, or where at-work charging is enabled). The use of cross-sectional drive patterns were once again found to provide an inconsistent representation of the economics of the underlying individual vehicles, leading us to conclude that longitudinal vehicle- or driver-specific drive patterns must be treated independently if an accurate and meaningful economic analysis is to be performed for PHEVs. However, the smaller sensitivity to drive patterns implies that the associated errors are less severe than they can be with BEVs.

Regarding vehicle architecture and use strategy, we find that the method of available energy management and the election of right-away or just-in-time charge timing generally have a small impact on the TCO of PHEVs. AER and the maximum allowed SOC also had a smaller than expected effect considered independently. When combined with the opportunity to charge at work, though, these three factors can reduce the 75th percentile PHEV-to-CV cost ratio by 16%, implying a considerable reduction in TCO for many drive patterns when a PHEV is employed over a CV. However, in the presence of high battery prices, the absence of federal incentives, or reduced gas price forecasts—conditions which we did not explore—we might expect the relative cost-effectiveness of a PHEV to suffer and sensitivity to AER and maximum allowed SOC to increase.

Regarding gasoline savings, we find that the PHEVs considered herein have the ability to have a very strong impact on gasoline consumption. Our analysis of the PHEV45 shows that the top 25% of

the most cost effective drive patterns would see an average reduction of 84% of gasoline consumption versus a 32 mpg CV. This value decreases with AER to 48% for the PHEV15. Given that we find a much lower correlation of TCO to AER once batteries have reached the U.S. Department of Energy's 2015 cost targets, these longer range PHEVs appear to be a better value than the short-range PHEVs when reducing gasoline consumption is a primary objective.

As highlighted earlier, this study should not be treated as an evaluation of any specific technology targets, nor a comparison of any specific manufacturer's vehicle models, due to discrepancies in vehicle platforms, control strategies, and other factors between our assumptions, the assumptions used for target selection, and actual available vehicle values. Further, this study has not been designed to gauge the likelihood of consumer acceptance of PHEVs, which may be more sensitive to payback periods than TCO or other non-economic factors. Rather, our primary intent has been to illuminate economic trends and sensitivities across PHEVs of various AERs when different charge strategies are employed. That being said, we note that many of our assumptions are similar to those employed for the United States Advanced Battery Consortium's 40 mile PHEV targets. Our findings thereby lend some support to the persistence of this target on the basis that, although it may not be the least expensive configuration in terms of TCO, it does offer the potential to greatly reduce gasoline consumption rates while still offering considerable savings over a CV.

Acknowledgment

This study was supported by Dave Howell and Brian Cunningham of the Energy Storage, Vehicle Technologies Program, Office of Energy Efficiency and Renewable Energy, U.S. Department of Energy. The use of the battery degradation and FASTSim vehicle simulation tools, both developed at the National Renewable Energy Laboratory under funding from the U.S. Department of Energy's Vehicle Technologies Program, was critical to the completion of this study. Special thanks to Michael O'Keefe, Caley Johnson, and Michael Mendelsohn for all their work framing and developing the Battery Ownership Model; Kandler Smith for developing and supporting the integration of the battery degradation model; and Ahmad Pesaran, the National Renewable Energy Laboratory's Energy Storage team leader, for his continual guidance.

References

[1] Michael O'Keefe, Aaron Brooker, Caley Johnson, Mike Mendelsohn, Jeremy Neubauer, Ahmad Pesaran, Battery Ownership Model: A Tool for Evaluating the Economics of Electrified Vehicles and Related Infrastructure, The 25th International Battery, Hybrid, and Fuel Cell Electric Vehicle Symposium and Exposition, Shenzhen, China, November 2010.
[2] Plug-In Electric Vehicle Credit (IRC 30 and IRC 30D). http://www.irs.gov/businesses/article/0, id=214841,00.html, (accessed 26.01.12).
[3] Kandler Smith, Tony Markel, Gi-Heon Kim, Ahmad Pesaran, Design of Electric Drive Vehicle Batteries for Long Life and Low Cost, IEEE Accelerated Stress Testing and Reliability Workshop, Denver, CO, October 2010.
[4] Conversation with Mike Ferry, California Center for Sustainable Energy, 8 Dec 2011.
[5] Annual Energy Outlook 2010 with Projections to 2035, U.S. Energy Information Administration, April 2010, DOE/EIA-0383(2010).
[6] http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMM_EPMR_PTE_NUS_DPG&f=W, (accessed 3.10.11).
[7] Li Zhang, Tim Brown, G. Scott Samuelsen, Journal of Power Sources 196 (15) (1 August 2011) 6559–6566.
[8] Utility Factor Definitions for Plug-in Hybrid Electric Vehicles Using Travel Survey Data, SAE, 2010, J2841 revision A.
[9] http://www.gpo.gov/fdsys/pkg/FR-2011-07-06/html/2011-14291.htm, (accessed 22.09.11).
[10] H. Lohse-Busch, Small EV Testing and Analysis, Presentation to DOE, Argonne National Laboratory, November 17, 2009.
[11] www.aaaexchange.com/assets/files/201048935480.Driving%20Costs%202010.pdf, (accessed 14.11.11).
[12] David Howell, Annual Merit Review: Energy Storage R&D and ARRA Overview (March 2011). http://www1.eere.energy.gov/vehiclesandfuels/pdfs/merit_review_2010/electrochemical_storage/es00a_howell_2010_o.pdf, (accessed 03.10.11).
[13] Electrical and Electronics Technical Team Roadmap (Dec. 2010). http://www1.eere.energy.gov/vehiclesandfuels/pdfs/program/eett_roadmap_12-7-10.pdf, (accessed 21.09.11).
[14] Alex Rogozhin, Michael Galaher, Gloria Helfand, Walter McManus, Int. J. Prod. Econ. 124 (2) (April 2010) 360–368.
[15] A. Vyas, D. Santini, R. Cuenca, Comparison of Indirect Cost Multipliers for Manufacturing, Center for Transportation Research, Energy Systems Division, Argonne National Laboratory, Argonne, IL, April 2000.
[16] Sierra Research, Inc., Study of Industry-average Mark-up Factors Used to Estimate Changes in Retail Price Equivalent (RPE) for Automotive Fuel Economy and Emissions Control Systems, Sierra Research, Inc., Sacramento, CA, November 21, 2007.
[17] Neubauer, Jeremy, Eric Wood, Aaron Brooker, Sensitivity of battery electric vehicle economics to drive patterns, vehicle range, and charge strategies, J. Power Sources, (in print).
[18] Traffic Choices Study—Summary Report, Puget Sound Regional Council, April 2008.
[19] National Household Transportation Survey. Available from: www.nhts.ornl.gov. (accessed 12.02.10).
[20] Aaron Brooker, M. Thornton, J. Rugh, Technology Improvement Pathways to Cost-Effective Vehicle Electrification", SAE 2010 World Congress, Detroit, MI, April 2010.
[21] United States Advanced Battery Consortium LLC, Development of Advanced High Performance Batteries for Plug-in Hybrid Electric Vehicle (PHEV) Applications (December 2009). Detroit, MI.
[22] Ahmad Pesaran, Tony Markel, H.S. Tataria, David Howell, Battery Requirements for Plug-in Hybrid Electric Vehicles: Analysis and Rationale, 23rd International Electric Vehicles Symposium and Exposition, Anaheim, CA, December 2007.

Glossary

AER: all electric range
BEV: battery electric vehicle
BOM: Battery Ownership Model
CS1: charge strategy 1 (right-away charge from home)
CS2: charge strategy 2 (just-in-time charge from home)
CS3: charge strategy 3 (just-in-time charge from home, right-away charge from work)
CV: conventional vehicle
DOD: depth of discharge
DVMT: daily vehicle miles traveled
EIA: Energy Information Administration
PDF: probability density function
PHEV: plug-in hybrid electric vehicle
SOC: state of charge
TCO: total cost of ownership
TCS: Traffic Choices Study
VMT: vehicle miles traveled